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Technical analysis and the strategy-based portfolio versus random one

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Abstract

Market participants use different tools basically technical or fundamental analysis to have a higher return in constructing a well-maintained portfolio. Examining the efficiency of technical strategies in creating a portfolio is the main objective of this study. Technical analysis is based on using historical trading data to launch selling and buying rules that maximize return and still control risks of loss. We use the adjusted trading data of 50 active stocks in the Tehran Stock Exchange as our sample which includes daily trading data from 2008 to 2019. We construct two types of portfolio; strategy-based portfolio versus random one. Then we calculate abnormal returns of each type of portfolio, applying the Monte-Carlo technique. Using Independent-Samples T-Test to compare means of the abnormal returns, our findings show that there is a significant positive abnormal return for both strategies applied in constructing a portfolio (0.057 and 0.062 mean difference for the first and second strategy, respectively), confirming the higher efficiency of applying technical strategies in portfolio management. Therefore, it is suggested to have and apply a strategy or combination of strategies for trading as an active participant, instead of constructing, rebalancing and maintaining one's portfolio only by chance, since there will be undesirable results in the long-run.

Keywords: Monte-Carlo Technique, Random portfolio, Strategy-based portfolio, Technical analysis.

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Introduction

The portfolio management process is an integral set of steps undertaken in a consistent manner to create and maintain an appropriate portfolio to meet the stated goals. Traders use different analysis such a technical or fundamental analysis to find a better solution in selecting a combination of assets as their investment portfolio. Many researches have focused on how to defeat the market by gaining higher returns at a pre-defined level of risk. Defining a trading strategy by using available information such as historical data to establish specific rules for buying and selling stocks with the objective of maximizing return and minimizing risk is the final goal of a capital market participant such as the investment managers. But here is a question: could we get higher abnormal returns by applying common trading strategies versus creating random portfolios.

An investor who follows a bottom-up approach to active investing focuses either on (1) technical aspects of the market or (2) the economic and financial analysis of individual companies, giving relatively less weight to the significance of economic and market cycles. The investor who pursues a bottom-up strategy based on certain technical aspects of the market is said to be basing stock selection on technical analysis. The primary research tool used for investing based on economic and financial analysis of companies is called security analysis. (Frank J. Fabozzi and Harry M. Markowitz (editors), 2002).

Many researches have been done on comparing the efficiency of application of few technical indicators such as moving averages with the buy and hold strategy based portfolio, but none of them has compared the abnormal returns of technical-based portfolios with those of completely random portfolios assuming random selection of a number of assets in the portfolio in different holding periods such as short-term, mid-term or long-term. In this study, abnormal return means portfolio returns minus TEPIX[1] return in the same holding periods while constructing a portfolio.The main focus of this study is to test statistically the difference of two groups of abnormal returns, one for the portfolios constructed with technical strategies and the other for the random portfolios. In each group, portfolio returns are subtracted from the index portfolio return. Here, the index portfolio returns for the specific time horizons (for example short-terms) are not the same because of the different holding days and weights for each of the portfolios. There is not any similar study yet in IRAN capital market.

1. Tehran stock exchange index

Literature Review

Technical analysis is based on using historical trading data to launch selling and buying rules that maximize return and still control risks of loss. Conversely, based on EMH[2], this endeavor is eventually unworkable. We cannot defeat the market by gaining abnormal return than the market return since the EMH indicates that all relevant and available information are already integrated with the security prices (Jahankhani, A & Abdoh Tabrizi, H.,1993).

As technical analysis uses only past and current trading data, it is impossible to attain abnormal positive returns by applying these technical trading procedures. If investors could create money from applying these trading procedures, this would designate that the market is inefficient. Hence, the question of whether technical trading rules can reliably create returns becomes an empirical and theoretical issue concerning the efficiency of stock markets (Masry, M., 2017).

Before discussing the theoretical framework of technical analysis, it is necessary to define what technical analysis is. Technical analysis is the knowledge of recording, typically in graphic form, the actual history of trading (volume of transactions, price changes) in a definite stock or "in the Averages" and then realizing from that pictured history the possible future trend. (Edwards R. D., & Magee J. ,1997).

Furthermore, technical analysis is the learning of market action, mainly using charts, for the sake of predicting upcoming price trends. Market action refers to three sources of information, accessible to the technician, i.e., volume, price and open interest (which is the total number of outstanding derivative contracts, such as options or futures that have not been settled for an asset). This action is the consequence of the mass behavior of buyers and sellers or rather, crowd behavior (Murphy, 1999).

While Charles, D., Kirkpatric, J., & Dahlquistk, A. (2016) define technical analysis as the study of historical market data, mainly volume data and price, this information is used to make investment decisions or trading.

Besides, Achelis, Steven B. (2001) defines technical analysis as the method of analyzing historical data in an effort to expect possible future prices.Technical Analysis patterns grade from simple approaches to more complex, it is a term including numerous strategies forecasting patterns and directions of stock prices (Peterson, 2006).

2. Efficiency Market Hypothesis

Users of technical analysis are Chartists, as they mainly depend on charts, they think that history tends to repeat them, thus they can use these patterns in predicting stock prices (Gencay, 1998). Although there is no reason explaining why patterns are repeated, TA approach determines the time of direction changing (Upwards or Downwards), which helps the investor to choose a suitable time to enter or exit from the market. Others see that TA is a reflection of the notion that prices are moving in the direction according to the change in investors ‘attitudes towards the political, economic and monetary situations. Evident skill technical analyst is to identify trend changes at an early stage and to use this knowledge in the formulation of appropriate strategies until the appearance of evidence that proves the trend is fluctuating (Cheol-HO, P., & Scott, H. I. , 2007).

In summary, the value of the technical analysis comes from the fact that current market statics are not enough to transmit information, comparing previous prices to current ones is not enough to enable investors to have more assessments that are accurate. On the other hand, the market volume provides decision-makers with information about the quality of traders details, which cannot be defined through prices, as both market volume and prices provide together more valuable information than just observing prices, whereas main information which affects the price - economic, political, psychological – come from the volume of transactions and prices of securities. From the above, it can be concluded that most of the above-mentioned definitions contain two or more of the three following points:

- Prices move in trends.
- History repeats itself.
- Market action discounts everything.

In short, TA analyses the history of past trends to evaluate investments nowadays, this philosophy is based on above-mentioned three points that allow studying charts and current data so one can expect future market directions.

The earlier literature on stock returns finds evidence that daily, weekly and monthly returns are predictable from past returns. Pesaran and Timmermann (1994) present further recent evidence on the predictability of abnormal returns on common stocks for the Standard and Poor’s 500 and the Dow Jones Industrial portfolios at the monthly, quarterly and annual frequencies. Pesaran and Timmermann (1995) examine the robustness of the evidence on the predictability of U.S stock returns and address the issue of whether this predictability could have been historically exploited by investors to earn profits more than a buy-and-hold strategy.

Evidence of the predictability of stock market returns led the researchers to investigate the sources of this predictability. In the study of the Brock, W., Lakonishok, J., & LeBaron, B., (1992), two of the simplest and most popular trading rules, moving average and the trading range break rules, are tested through the use of bootstrap techniques. They compare the returns conditional on buy (sell) signals from the actual Dow Jones Industrial Average Index to returns from simulated series generated from four popular null models. These null models are the random walk, the AR[3] (1), the GARCH-M[4] due to Engle, Lilien and Robins (1987) and the EGARCH developed by Nelson (1991). They find that returns obtained from buy (sell) signals are not likely to be generated by these four popular null models. The document that buys signals generates higher returns than sell signals and the returns following buy signals are less volatile than returns on sell signals. They do not investigate the profitability of technical rules after realistic commissions, as they focused their attention on a bootstrapped-based view for specification testing. However, the results document two important stylized facts. The first is that buy signals consistently generate higher returns than sell signals. The second is that the second moments of the distribution of the buy and sell signals behave quite differently because the returns following buy signals are less volatile than returns following sell signals. The asymmetric nature of the returns and the volatility of the Dow series over the periods of buy and sell signals suggest the existence of nonlinearities as the data generation mechanism.

Setayesh and et al (2009) examined the application of technical indicators in forecasting the stock's trend in TSE. Results show that the buy and hold strategy has a higher return in comparison with technically based returns using RSI[5], MFI[6], DMI[7], IMI[8], WIL[9], but technical signals using TMA[10], VMA[11], EMA[12], WMA[13], SMA[14] show significantly better results comparing with buy

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3. Autoregressive
4. generalized autoregressive conditional heteroskedasticity-in-mean
5. Relative Strength Index
6. Money Flow Index
7. Dynamic Momentum Index
8. Intraday Momentum Index
9. Williams %R
10. Triangular Moving Average
11. Variable Moving Average
12. Exponential Moving Average

and hold strategy.

Tehrani and Esmaili (2011) examined the effects of using common technical indicators on short term returns of investors in TSE. Their findings show that the sole using of technical indicators do not have a better performance than the buy and hold strategy, but using a combination of indicators could have a better result. MFI and Bollinger Bands are among the weakest technical indicators.

Saleh Ardestani and Varzeshkar (2015) examined the returns of fundamental versus technical based security selection in portfolio creation. Their findings show that fundamental analysis is more profitable than the technical analysis.

Pourzamani and Rezvani (2016) examined the efficiency of technical strategies using an exponential moving average and relative strength index on daily and weekly data for 16 investment companies for 5 years in TSE. This study shows that technical strategies have not enough efficiency in bullish markets but better in bearish markets.

Rostami, M.R., Alipour P. and Behzadi, A. (2018) analyzed the causal relations between trading volume and stock returns and between trading volume and return volatility in TSE. According to the results, no bilateral causal relationship can be ascertained between returns, volume, and return volatility. In other words, return and return volatility could barely predict volume; therefore, the volume cannot be the Granger causality of the other two variables. However, stock returns were found to have an important role in determining the volume. Likewise, return volatility can be used to predict volume accurately. In fact, stock returns and the return volatility were both the Granger causalities of the volume.

Bajalan, S., Eyvazlu, R. & Akbari, Guilda (2018), use a pair trading strategy to make a profit in an emerging market using smooth transition heteroskedastic models for producing thresholds as trading entry and exit signals. This is a statistical arbitrage strategy used for similar assets with dissimilar valuations. For generating upper and lower bounds, they have applied the rolling window approach and one-step-ahead quantile forecasting. Markov chain Monte Carlo sampling method is used for optimizing the parameters. Also, a passive strategy in the out-of-sample period is used to

13. Weighted Moving Averages

14. Simple Moving Averages

compare the profits. Their findings show strategy 1 and 2 have positive returns in the out-of-sample period, and they produce higher returns than a passive strategy.

Jafari samimi, A. and Asghar Tabar Ledari, M. (2017) found the optimum period of short term and long term moving averages using a genetic algorithm as the technical indicators of buy and sell signals.

In brief, throughout the literature review of this study, it is clear that the empirical framework of the study has the lack of research in which the abnormal positive return of a common strategies-based portfolio is going to be compared with that of a random portfolio which is a usual style of the many new practitioners with or without knowledge of finance in growing capital market of IRAN.

As seen in the literature, most of the related studies compared the usefulness of technical analysis versus buy and hold strategy not the returns of the random portfolios. Hence, the following hypothesis is developed in this study:

Hypothesis: There is a significant positive abnormal return for Strategy-based Portfolios versus Random one.

Methodology

The sample includes daily trading data of the 50 active stocks in TSE. Given the experiences in international stock exchanges, identifying top companies is often based on the stock liquidity, market capitalization and superiority of financial ratios. Accordingly, identifying more active companies in Tehran Stock Exchange is based on a combination of stock liquidity, trading volume, frequency of trading and the market capitalization which is calculated and updated quarterly.

To test the above-mentioned hypothesis, we should process the raw daily trading data to create two samples of portfolios, then calculate the abnormal returns of the two types of the portfolio, strategy-based versus random one. Our sample includes daily trading data of the 50 active stocks and TEPIX from 2008 to 2019, gathered from Rahavard Novin software. At first, we've defined technical strategies as the different templates in Meta Stock software. Then we defined buy and sell signals of the sample period. Finally, we processed data in Excel and tested in SPSS.

These portfolios were created within the different predefined investment time horizons (holding period up to 20 days represents for monthly or very short term time horizon, from 21 to 60 days represents for quarterly or short term time horizon, from 61 to 180 days represents for semiannually or mid-term time horizon and more than 181 days represents for long-run time horizon). As we have created 10000 random time horizon with equal probability, thus there are 2500 portfolios in each category of periods approximately.

To explain in more details, we are going to generate two groups of abnormal returns, one for the strategy-based portfolios and the other for the random portfolios. In each group, abnormal returns will be calculated as stock portfolio returns (technical-based or random) minus index portfolio returns in exactly the same holding period. The point is that the index portfolio returns for both groups are not equal, although they are in the same time categories. For example, we are going to create and calculate two sample portfolios with 3 assets and then calculate the abnormal returns:

Table1. Random Portfolio- Number 1

Time Horizon(random)	Quarterly(20<Holding Period<60)		
Asset(random)	D	A	H
Weight(random)	0.17	0.27	0.3
Date of Buying(random)	2/12/2018	2/18/2018	2/13/2018
Date of selling(random)	3/25/2018	4/22/2018	3/29/2018
Holding Period(#days)	41	63	44
Buying-day close price	1,580	3,270	2,310
Selling-day close price	1,320	3,860	2,497
Logarithmic Return	-0.180	0.166	0.078
Total stock portfolio Return	**0.038**		
Buying-day TEPIX	214,010	214,650	213,960
Selling-day TEPIX	228,500	231,560	229,550
TEPIX Return	0.066	0.076	0.070
Total index portfolio Return	**0.053**		
Abnormal Return	**-0.015**		

Strategy-based Portfolio A:

Table2. Strategy Based Portfolio-Number 1

Time Horizon(random)	Quarterly(20<Holding Period<60)		
Asset(random)	A	B	C
Weight(equal weights)	0.33	0.33	0.33
Date of Buying(signal-based)	1/20/2018	1/27/2018	1/29/2018
Date of selling(signal-based)	2/25/2018	3/20/2018	3/17/2018
Holding Period(#days)	36	52	47
Buying-day close price	2,100	5,150	1,270
Selling-day close price	2,270	5,520	1,320
Logarithmic Return	0.078	0.069	0.039
Total stock portfolio Return	**0.062**		
Buying-day TEPIX	210,500	211,000	211,350
Selling-day TEPIX	212,750	214,653	213,000
TEPIX Return	0.011	0.017	0.008
Total index portfolio Return	**0.012**		
Abnormal Return	**0.05**		

Implementing Monte-Carlo Technique, here are the steps to construct the random portfolio:

1- To be able to search and select easier the same stock for selling at the same time horizon randomly, trading data were sorted based on the historical daily transactions of each stock. There were 88,559 trading days in total. Now, you can randomly lookup for a date in a predefined 20-days holding period (from the next trading day to the 20^{th} trading day of the selected stock).

2- Generate 10,000 random numbers from this dataset {3, 5, 7, 10} as the number of assets in the portfolio. As the probabilities of the portfolios are equal, approximately there will be 2500 3-assets portfolios and 2500 5-assets portfolios and so on.

3- Generate 10,000 random maximum investment time horizon up to 20 days (represents monthly holding period), 60 days (represents quarterly holding period), 120 days (represents semiannually holding period) and 240 days (represents yearly holding period).

4- Generate 10,000 random numbers between 1 to 88559 as the first asset of each portfolio and lookup the related close price of the stock in that day as the buying point.

5- Select randomly a close price of the stock selected in stage 4 from the next day of the buying-date until the ending date of the randomly selected holding period (generated and defined in stage 3). For example, if you have selected randomly close price of the "Kegol" symbol in 2015/02/15 as your first asset' buying date for a randomly selected 20-days holing period, now you can select randomly a close price of "Kegol" symbol from 201/02/16 to 2015/03/16(assuming 10 days for weekends) as your selling date.

6- Then calculate the holding period return by formula 1:

$$\mathrm{R_i} = \mathrm{LN}\left(\frac{\text{selling day close price}}{\text{buying day close price}}\right) \tag{1}$$

7- Start the process of selecting the next random asset from the first buying day till the ending day of the randomly selected holding period.

8- Repeating the process defined in stages 6-7 up to the maximum assets randomly selected based on the process defined in stage 2.

9- Generate a random number between 0 and 1 up to the number of the stocks in the portfolio (defined in stage 2) plus 1 for the Cash left in each time of a portfolio generation.

10- Divide each random number to the sum of the random numbers for each portfolio to make their sum equal to 1.

11- In each row of the sheet, we have N values for returns and N+1weights. The last value for the weight is dedicated to the cash left after random portfolio generation with a return of zero.

12- Simply we can calculate the portfolio returns with this formula:

$$\text{STOCK PR}_{\mathrm{i,t}} = \sum_{i=1,t=1}^{N,M} \mathrm{R_{i,t}} \times \mathrm{W_{i,t}} \tag{2}$$

13- Now we should calculate the index portfolio return in the same holding periods while creating our stock portfolio. For example, for a 3-asset portfolio with different holding times and weights, we should calculate the weighted index return for the same periods as shown in table 1.

$$\text{TEPIX PR}_{\mathrm{i,t}} = \sum_{i=1}^{N} \text{Tepix Return}_{,\mathrm{t}} \times \mathrm{W_{i,t}} \tag{3}$$

14- Abnormal returns of each portfolio are calculated with the formula (4) based on the example explained in Table 1.

$$\text{Abnormal Return for random portfolio}_{,\mathrm{t}} = \text{STOCK PR}_{\mathrm{i,t}} - \text{TEPIX PR}_{\mathrm{i,t}} \tag{4}$$

We have 10,000 abnormal returns for 10,000 random portfolios. To have a strategy-based portfolio, first of all, we should define different sets of technical indicators and oscillators as our strategies to find buying and selling signals. After reviewing the definition of applied technical indicators and oscillators in this paper, we will introduce the two sets of strategies for different market conditions as below:

Technical indicators and oscillators

EMA

The exponential moving average is calculated by applying a percentage of today's close price to yesterday's moving average value. EMA places more weight on recent price. The formula is:

$$\text{Exponential Percentage} = \frac{2}{Time\ Periods + 1} \tag{5}$$

$$\text{EMA} = (Today'sclose \times Exponential\ Percentage) + (\text{Yesterday'sMoving Average} \times (1 - \text{E}xponential\ Percentage)) \tag{6}$$

RSI

The relative strength index is a momentum indicator which is a line graph that moves between two extremes (0 to 100) that measure the magnitude of recent price changes to evaluate overbought or oversold conditions with values of 80 or above indicate that a security is becoming overbought and with a value of 20 or below indicates an oversold or undervalued condition. The standard is to use 14 periods to calculate the initial RSI value:

$$\text{RSI}=100 - \left[\frac{100}{1+\frac{Average\ Gain}{Average\ Loss}}\right] \tag{7}$$

arabolic SAR

The parabolic SAR is a technical indicator which appears as a series of dots placed either above the bars as a bearish signal or below the price bars as a bullish signal.

The general formula used for this is:

$$SAR_{n+1} = SAR_n + \alpha\ (EP - SAR_n) \tag{8}$$

Where:

SAR_n &SAR_{n+1}: the current period and the next period's SAR values.

EP (the extreme point): is a record kept during each trend that represents the highest value reached by the price during the current uptrend or lowest value during a downtrend. During each period, if a new maximum (or minimum) is observed, the EP is updated with that value.

α: the value represents the acceleration factor. Usually, is set to a value of 0.02

CCI

The Commodity Channel Index is a momentum-based oscillator used to determine the overbought and oversold conditions. CCI above (below) zero indicates the price is above (below) the historic average. It is calculated by this formula:

$$CCI = \frac{Typical\ Price - MA}{0.15\ \times Mean\ Deviation} \tag{9}$$

Where:

Typical Price =$\sum_{i=1}^{P}((High + Low + close) \div 3)$

P = Number of periods

MA = Moving Average

Moving Average = $(\sum_{i=1}^{P} Typical\ Price) \div P$

Mean Deviation = $(\sum_{i=1}^{P} |Typical\ Price - MA|\ \div P$

ADX

The average directional index is primarily an indicator of momentum or trend strength, but the total ADX system is also used as a directional indicator.

The +DM and -DM are found by calculating the "up-move," or current high minus the previous high, and "down-move," or current low minus the previous low. If the up-move is greater than the down-move and greater than zero, the +DM equals the up-move; otherwise, it equals zero. If the down-move is greater than the up-move and greater than zero, the -DM equals the down-move; otherwise, it equals zero.

Then +DI equals 100 times EMA of +DM divided by the average true range over a given number of periods. Welles usually used 14 periods. The negative directional indicator, or -DI, equals 100 times EMA of -DM divided by the average true range (ATR). The ADX indicator itself equals 100 times the exponential moving average of the absolute value of (+DI minus -DI) divided by (+DI plus -DI).

If +DI is the higher number, market direction is up; if -DI is the greater number, market direction is down. The ADX indicator, which varies in value from zero to 100, is the primary momentum indicator. A value over 20 indicates the existence of a trend; a value over 40 indicates a strong trend.

Stochastic Oscillator

It's a momentum indicator comparing a particular closing price of a security to a range of its prices over a certain period of time with two bands, readings over 80 are considered in the overbought range, and readings fewer than 20 are considered oversold. The formula is:

$$\%K = \left(\frac{C - L14}{H14 - L14}\right) \times 100 \tag{10}$$

Where:

C = the most recent closing price

L14 = the lowest price traded of the 14 previous trading sessions

H14 = the highest price traded during the same14- day period

%K = the current value of the stochastic indicator

%K is referred to sometimes as the slow stochastic indicator. The "fast" stochastic indicator is taken as %D = 3-period moving average of %K.

Ichimoku clouds

It is a collection of five lines, two of which compose a cloud that shows support and resistance levels, as well as momentum and trend direction. When a price is below the cloud the trend is down. When a price is above the cloud the trend is up. The formulas for the lines are as below:

$$\text{Conversion Line(kenkan sen)} = \frac{\text{9 period high} + \text{9 period low}}{2} \tag{11}$$

$$\text{Base Line(kijiun sen)} = \frac{\text{26 period high} + \text{26 period low}}{2} \tag{12}$$

$$\text{Leading Span A(senkou span A)} = \frac{\text{Conversion line+Base Line}}{2} \qquad (13)$$

$$\text{Leading Span B(senkou span B)} = \frac{\text{52 period high} + \text{52 period low}}{2} \qquad (14)$$

$$\text{n(chikou span)} = \text{Closeplotted 26 periods in the past}$$

Strategy1.

Buy signal	1)Close Price $>$ EMA$_{14}$ $>$ EMA$_{30}$ $>$ EMA$_{50}$ 2) Close Prices above the green Ichimoku clouds as the support zone 3)RSI$_9$ ≥ 70 4) ADX $\geq_{14}$ 20 & $DI^{+} > DI^{-}$ +& Upward trend ADX$_{14}$ & DI^{+}
Sell signal	$Close\ Price < EMA_{30}$ (No need for more conditions, since it was backtested and selected as the optimal exit signal)

Strategy2.

Buy signal	1)Close Price $>$ EMA$_{120}$ 2) Bullish signal for Parabolic SAR: A dot below the close price 3) CCI $breaking\ line$ 0 upward 4)$Stochastic\ Oscillator\ breaking\ line$ + 20 Upward
Sell signal	1) Bearish signal for Parabolic SAR: A dot above the close price 2) CCI $breaking\ line$ 0 downward 3) $Stochastic\ Oscillator\ breaking\ line$ + 80 downward

Here are the steps to follow to create a strategy-based portfolio:

1- Get the raw daily transactions of the sample from 2008 to 2019 from Rahavard Novin.
2- Define the set of technical indicators and oscillators as different templates in Meta Stock software.
3- Search, find and record the date of the buy and sell signals, respectively for the whole period separately.
4- Look up the close price of the day we got buy and sell signals.
5- Calculate the logarithmic return form the formula mentioned before for each of the signals.
6- Calculate the holding period by using the "Datedif" function in Excel.
7- Categorize the holding periods into 4 groups of below 20 days, below 60 days, below 120 days, more than 120 days.
8- Based on the Monte-Carlo Technique, start to create a random portfolio from this sheet of predefined technical-based trading. This time just randomly select the row of the trading signals and find the related returns up to the random number of assets in the portfolio in a random category of holding period.

9- Allocate equal weights according to the number of assets in the portfolio, for example, 0.2 for each asset in a portfolio with 5 stocks.

10- calculate the technical portfolio returns with this formula:

$$\mathrm{STOCK\ TPR_{i,t}} = \sum_{i=1,t=1}^{N,M} \mathrm{R_{i,t}} \times \mathrm{W_{i,t}} \tag{16}$$

Now we should calculate the index portfolio return in the same holding periods while creating our stock portfolio. For example, for a 3-asset portfolio with different holding times and weights, we should calculate the weighted index return for the same periods as shown in table 1.

$$\mathrm{TEPIX\ PR_{i,t}} = \sum_{i=1}^{N} \mathrm{Tepix\ Return_{i,t}} \times \mathrm{W_{i,t}} \tag{17}$$

11- Abnormal returns of each portfolio are calculated with the formula (4):

$$\begin{aligned}&\mathrm{Abnormal\ Return\ for\ strategy\ based\ portfolio_{,t}}\\ &\qquad = \mathrm{STOCK\ TPR_{i,t}} - \mathrm{TEPIX\ PR_{i,t}}\end{aligned} \tag{18}$$

Research Findings

Now we have two samples of abnormal returns, technical-based versus random one. We use the Independent-Samples T-Test to compare means. Results are presented in table 1 and table 2.

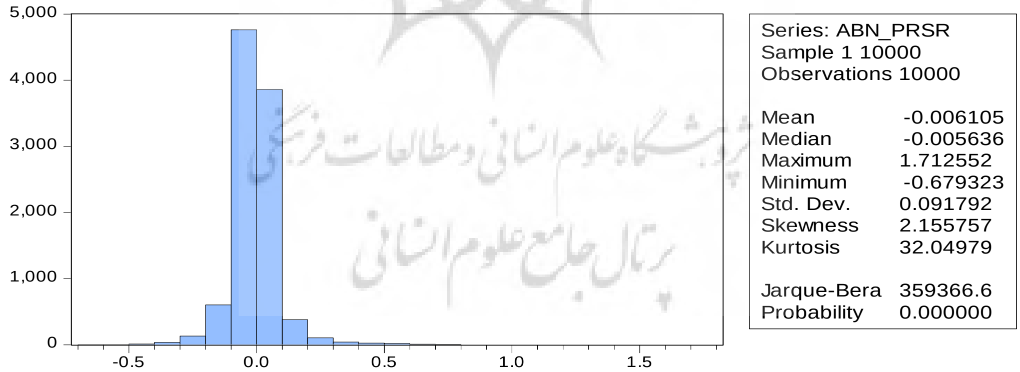

Figure 1. Descriptive statistics of Random Portfolios' Abnormal Returns

(For 2500 monthly, 2500 quarterly, 2500 semiannually, 2500 more than semiannual portfolios)

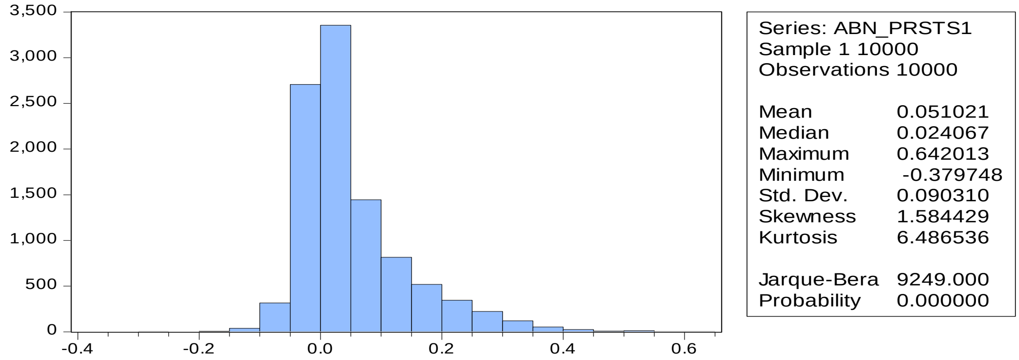

Figure 2. Descriptive statistics of Technical-based Portfolios' Abnormal Returns- Strategy 1

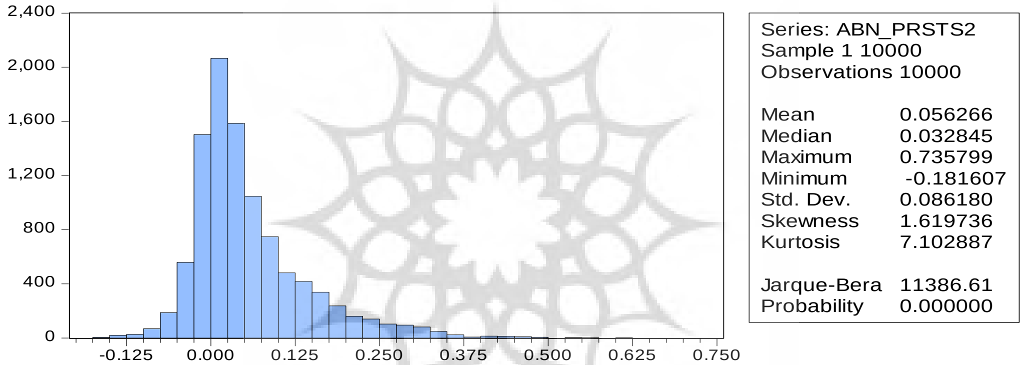

Figure 3. Descriptive statistics of 1st Technical-based Portfolios' Abnormal Returns- Strategy 2

To test the hypothesis, we use the two-sample T-Test to test the null hypothesis that the population means of two groups are equal, based on samples from each of the two groups. So, as constructed, the two-sample t-test assumes normality of the X in the two groups. In fact, as the sample size in the two groups gets large, which are 10,000 in this paper, the t-test is valid even when X doesn't follow a normal distribution. Because of the central limit theorem, the distribution of these, in repeated sampling, converges to a normal distribution of X in the population. Also, the estimator that the t-test uses for the standard error of the sample means is consistent irrespective of the distribution of X, and so it is unaffected by normality. As a consequence, the test statistic continues to follow an N (0, 1) distribution, under the null hypothesis, when the sample size tends to infinity.

Levene’s test is used to test whether the variances of the two samples are approximately equal. The null hypothesis is that there is no difference between the variance of the first group and the variance of the second group. We would like Levene's test to be non-significant. Levene’s test is an F test. As the sig. is less than 0.05, Levene's test is significant, so equal variances are not assumed. But as long as $N > 30$ and $n_1 \cong n_2$, the t-test is robust to violations of the homogeneity of variance.

Table1. Test of Homogeneity of Variances between Strategy-1 based and Random Abnormal Returns

		Levene Statistic	df1	df2	Sig.
Abnormal Returns	Based on Mean	230.8	1	19998	.000
	Based on Median	101.3	1	19998	.000
	Based on Median and with adjusted df	101.3	1	19904.9	.000
	Based on trimmed mean	162.9	1	19998	.000

To test hypothesis 1 we use the t-test assuming unequal variances defining as:

$$H_0: \mu_1 = \mu_2$$

$$H_1: \mu_1 \neq \mu_2$$

Assuming unequal variances, in table 3, we see the t-Test is significant in the significance level of $\alpha = 0.05$ and we reject the null hypothesis that the mean of the two groups is significantly equal. Hence, based on the positive mean of 0.0510 for the first group (Abnormal returns for Strategy-1 based Technical Portfolios) shown in table 2, we conclude that there are positive significant abnormal returns for strategy-1 based portfolios in comparison with creating random portfolios.

Table2. Descriptive Statistics

Group 1. Strategy-1 based technical Portfolio

Group-2.Random Portfolio

	Groups	N	Mean	Std. Deviation	Std. Error Mean
Abnormal Returns	1	10000	.0510	.0903	.0009
	2	10000	-.006	.0917	.0009

Table 3. Independent Samples Test

		Levene's Test		t-test for Equality of Means		
		F	Sig.	t	df	Sig. (2-tailed)
Abnormal Returns	Equal variances assumed	230.8	0.000	44.4	19998	0.000
	Equal variances not assumed			44.4	19992	0.000

*Mean difference: 0.057 for the unequal variances condition.

Table4. Test of Homogeneity of Variances between Strategy-2 based and Random Abnormal Returns

		Levene Statistic	df1	df2	Sig.
Abnormal Returns	Based on Mean	139.372	1	19998	.000
	Based on Median	64.193	1	19998	.000
	Based on Median and with adjusted df	64.193	1	19647.6	.000
	Based on trimmed mean	96.684	1	19998	.000

Same conclusions for the strategy-2 based technical portfolio abnormal returns versus random portfolio abnormal returns. It means that there are positive significant abnormal returns for strategy-2 based portfolios versus random portfolios.

Table4. Descriptive Statistics
Group 1. Strategy-2 based technical Portfolio
Group-2. Random Portfolio

Group	N	Mean	Std. Deviation	Std. Error
1	10000	.0562	.0862	.00086
2	10000	-.0061	.0918	.00092
Total	20000	.0251	.0943	.00067

Table 5. Independent Samples Test

		Levene's Test		t-test for Equality of Means		
		F	Sig.	t	df	Sig. (2-tailed)
Abnormal Returns	Equal variances assumed	139.3	0.000	49.5	19998	0.000
	Equal variances not assumed			49.5	19992	0.000

*Mean difference: 0.062 for the unequal variances condition.

Conclusion

Our findings show that there is a significant positive abnormal return between strategy-based portfolio versus random one. Using independent-samples T-Test to compare means of the two portfolio types, mean differences of abnormal returns are 0.057 and 0.062, respectively for the first and second strategies selected to construct technical portfolio versus random one. Therefore, it is suggested to have and apply a strategy or combination of strategies for trading as an active participant, instead of creating one's portfolio only by chance, as there will be undesirable results in the long-run.

Therefore, having a trading strategy and constructing one's portfolio based on technical strategies will result in better performance. In other words, to gain positive significant abnormal return (portfolio return minus index portfolio return), it is recommended to have a predefined trading strategy or combination of strategies.

It should also be mentioned that the results may be due to the selected database time frame and we need to consider a much larger time frame to achieve a more reliable result. One can use different technical strategies in portfolio construction with different sample data. In future studies, one can apply other dynamic algorithms to create different holding periods. International sanctions, currency jump, change of governments can be controlled in the model.

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